Architecture Overview

The **WeatherNetModel** is designed to predict weather parameters for a specific station by effectively capturing spatial and temporal dependencies from nearby stations.

The architecture integrates **1D Convolutional Neural Networks (CNNs)** for feature extraction, **positional encodings** for spatial and temporal context, and a **Transformer Encoder** to model complex interactions between stations and across time windows. The final prediction layer outputs the desired weather metrics.

Hybrid Model Approach

We employ a **multi-model strategy**, utilizing four instances of the **WeatherNetModel**, each optimized for different forecasting horizons. While all models share the same architecture, they specialize in distinct time frames to enhance predictive accuracy:

- **0–12 hours**: Captures short-term weather dynamics.
- **12–24 hours**: Provides insights into near-daily trends.
- **24–36 hours**: Focuses on mid-term patterns.
- **36–60 hours**: Optimized for longer-range forecasts.

By training each model on its respective time window, we ensure that learned representations are tailored to specific temporal dependencies, improving accuracy across different forecasting horizons.

Conclusion

The **WeatherNetModel** integrates **CNN-based feature extraction**, **positional encodings**, and **Transformer-based encoding** to deliver precise weather predictions for targeted stations. Its **modular design** ensures flexibility and scalability, making it well-suited for diverse meteorological applications. By leveraging both spatial and temporal contexts, the model significantly enhances predictive performance in complex weather systems.